Downloaded from orbit.dtu.dk on: May 05, 2023

DTU Library

Smart Grid Charging of Electric Vehicles: EV-Owner Response to Scheduling and Pricing under Myopic Loss Aversion in an Ultimatum Two-Player Game

Fetene, Gebeyehu Manie; Kaplan, Sigal; Sebald, Alexander Christopher; Prato, Carlo Giacomo

Published in:
Proceedings of the 94th Annual Meeting of the Transportation Research Board

Publication date:
2015

Document Version
Publisher's PDF, also known as Version of record

Link back to DTU Orbit

Citation (APA):
Fetene, G. M., Kaplan, S., Sebald, A. C., & Prato, C. G. (2015). Smart Grid Charging of Electric Vehicles: EV-Owner Response to Scheduling and Pricing under Myopic Loss Aversion in an Ultimatum Two-Player Game. In *Proceedings of the 94th Annual Meeting of the Transportation Research Board*

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Smart Grid Charging of Electric Vehicles: EV-Owner Response to Scheduling and Pricing under Myopic Loss Aversion in an Ultimatum Two-Player Game

Gebeyehu Manie Fetene *
Department of Transport
Technical University of Denmark
Bygningstorvet 116B, 2800 Kgs. Lyngby, Denmark
Tel: +45.4525.6524
Fax: +45.4593.6533
Email: gebefe@transport.dtu.dk

Sigal Kaplan
Department of Transport
Technical University of Denmark
Bygningstorvet 116B, 2800 Kgs. Lyngby, Denmark
Tel: + 45.4525.6559
Fax: +45.4593.6533
Email: siga@transport.dtu.dk

Alexander Christopher Sebald
Department of Economics
Copenhagen University
Øster Farigmagsgade 5, Bygning 26, 1353 København K
Tel: +45.3532.4418
Fax: +45.3532.3010
Email: alexander.sebald@econ.ku.dk

Carlo Giacomo Prato
Department of Transport
Technical University of Denmark
Bygningstorvet 116B, 2800 Kgs. Lyngby, Denmark
Tel: + 45.4525.6595
Fax: +45.4593.6533
Email: cgp@transport.dtu.dk

* corresponding author

Final manuscript for presentation at the 94th Annual Meeting of the Transportation Research Board, January 11-15, 2015, Washington D.C.

Submission date: November 12, 2014

Word count: 6736 (text) + 3 × 250 (figures and tables) = 7486

ABSTRACT

Upward expectations of future electric vehicle (EV) growth pose the question about the future load on the electricity grid. While the literature on demand side management of EV charging has focused on technical aspects and considered EV-owners as utility maximizers, this study looks at the neglected psychological dynamics of EV-owners facing charging decisions and interacting with the supplier. This study represents these dynamics by proposing a behavioral framework of utility maximization under myopic loss aversion within an ultimatum two-player game framework. The EV-owner and the electricity supplier are the two players, the EV-owner faces three decisions (i.e., whether to postpone the charging to off-peak periods, which discount to request to the supplier for off-peak charging, which discount to accept for supplier-controlled charging), and there are two contract durations where the EV-owner decides daily (short-term) or weekly (long-term). The experimental analysis included six treatment conditions from the combinations of the three decisions with the two contract durations, and results showed that: (i) EV-owners perform charging choices not as pure utility maximizers, but are affected by myopic loss aversion resulting from monetary considerations as well as the ultimatum game with the supplier; (ii) EV-owners are open towards centralized smart-grid strategies optimizing the load on the grid from a system optimum perspective; (iii) the frequency of charging decisions (daily versus weekly contract) favors on the one hand utility maximization behavior of EV-owners and induces on the other hand myopia with a favorable cost minimization for the supplier.

INTRODUCTION

While the market penetration of electric vehicles (EVs), including battery electric vehicles (BEVs), plug-in electric vehicles (PEVs), and plug-in hybrid electric vehicles (PHEVs), has been negligible so far because of high unit costs, limited driving range, and lack of recharging infrastructure, upward expectations exist for a future rapid EV growth following battery technology innovation and governmental commitment to EV promotion through investments, legislation, and taxation policies (e.g., *1*, *2*). While studies predict market shares around 4%-10% for BEVs and PHEVs by 2020 as reasonable (e.g., *2*, *3*, *4*), demand assessments suggest dominant market shares for EVs and PHEVs by 2030-2050 in both Europe and the U.S. (e.g., *4*, *5*, *6*, *7*). In Denmark, the future demand for EVs is estimated between 48% and 72% for new car buyers (*5*). In Belgium, a market share of 44% for BEVs and PHEVs could be attained by 2030 (*4*). In Iceland, EVs are expected to achieve between 48% and 93% of the total vehicle fleet by 2030 (*6*). In the U.S., EVs are estimated to achieve a market share exceeding 20% by 2030 and reaching 70%-80% by 2050 (*7*).

The future EV growth is expected to significantly load the electricity power grid. Even modest EV shares (20-25% of the total vehicle fleet) are expected to increase the electricity load by roughly 30% (*8*). Home EV charging is very important for the demand side management (DSM) of the electricity load, because both home charging availability relates to a higher likelihood of EV purchase and charging times occur off-peak overnight (*7*). Nevertheless, a major challenge in home EV charging is the scheduling to avoid congestion on the electricity grid. A recent survey in California has in fact showed that most EV charging is likely to start at 7pm during weekdays, namely during the seasonal peak electricity demand period (*9*). DSM of EV charging in a smart grid by encouraging EV-owners to change their charging patterns in response to changes in the electricity prices is viewed as a possible solution to avoid grid overload at demand peak hours and to delay the need for investments in increasing the grid capacity (*10*).

An ample body of research has addressed DSM from the economic and the logistic perspective. Economic studies focused on comparing smart and regular grid charging strategies while considering potential demand scenarios, centralized versus decentralized supplier electricity control, technological solutions for vehicle-to-grid (V2G) communication, time-of-use (TOU) pricing schemes and mobility patterns. Economic evaluations showed that cost savings for the customers and the suppliers are achieved with smart EV charging: smart charging grids in Finland produced benefits of 227 EUR per vehicle per year (*11*); shifting charging from peak to off-peak in the U.S. generated savings ranging from $1.1 billion to $5.1 billion per year (*12*); price-responsive charging strategies in Singapore turned estimated losses of 1000 SGD per vehicle per year into estimated profits of 21-130 SGD (*13*). Logistic studies concentrated on the optimization of EV charging from the system perspective while considering TOU pricing schemes, mobility patterns, and supplier's degree of system control, and controlling for constraints related to battery storage capacity and penalties for unserved driving needs: agent-based micro-simulation models estimated electricity prices varying with mobility behavior and optimal charging costs (*14*) and analyzed electricity demand considering EV potential demand and price schemes (*15*); optimization algorithms proposed efficient EV charging scheduling under system optimization or user utility maximization (e.g., *16*, *17*).

The major limitation in the aforementioned model lies in their focus being technical rather than socio-technical. EV-owners are assumed to be utility maximizers when facing long-term charging decisions, without stated-preference (SP) or revealed-preference (RP) surveys supporting this assumption. Psychological dynamics of EV-owners facing short-term versus long-term charging decisions and interacting with the supplier are neglected, as the only psychological aspects concern social etiquette (*18*) and resource replenishing behavior (*19*). This study contributes to the body-of-knowledge concerning EV charging by addressing these dynamics that are relevant to the DSM contract selection and, as the results show, are fundamental to the development of realistic agent-based and optimization models not affected by common psychological biases. This study addresses three key decisions by EV-owners: (i) whether to postpone the charging to off-peak periods; (ii) which discount to request to the supplier for off-peak charging; (iii) which discount to accept for supplier-controlled charging instead of own volitional control. Moreover, this study considers these decisions within two contract durations: (i) a daily contract where EV-owners may adapt their charging decision on the basis of immediate off-peak mobility needs; (ii) a weekly contract where EV-owners make a charging decision for a fixed time period. In a user-controlled system, EV-owners feel volitional control and a user utility maximization solution is obtained, while in a supplier-controlled system a system optimum solution can be reached. Accordingly, the contract selection requires bargaining between EV-owner and supplier, during which the EV-owner considers satisfaction related to volitional control, possible discounts proposed for off-peak charging, ability to reach an agreement based on the supplier’s acceptance of the discount, and potential losses for unforeseen mobility needs during off-peak periods.

With the intention to represent EV-owners’ charging decisions under these conditions, this study presents a novel behavioral framework of utility maximization under myopic loss aversion (MLA) in the context of an ultimatum game (UG). MLA combines the two concepts of loss aversion and mental accounting that lead individuals to risk averse behavior in short-term decisions (*20*). A UG is a sequential bargaining zero-sum game between two players (the proposer and the responder) bargaining over sharing a sum of money: the proposer presents a proposal about the sharing of the money, and the responder accepts or rejects the proposed shares (*21*). The behavioral framework leads to empirical stated-preference experiments covering six treatment conditions from the combinations of the three decisions with the two contract durations and verifying the manifestation of myopic behavior related to either the evaluation of the monetary gains or the participation in the bargaining. The novelty of the behavioral framework is not restricted to EV charging decisions: (i) while previous studies on MLA considered a single individual, this is the first study exploring MLA within a two-player UG and hence investigating MLA as related not only to the individual’s gains or losses, but also to the individual’s cautiousness in the proposal because of the need to consider the responder’s strategy (*22*); (ii) while previous studies on MLA considered only monetary decisions, this is the first study researching MLA for time-based decisions and hence looking into mental accounting for time as possibly similar to the one for money (*23*).

The paper is structured as follows. The next section presents the proposed behavioral framework. The following sections introduce the experimental design and illustrate the results of the three experiments on EV charging decisions. The last section draws conclusions and suggests policy implications.

BEHAVIORAL FRAMEWORK

This study proposes a novel behavioral framework involving utility maximization under MLA in the context of a UG.

MLA combines the two concepts of loss aversion and mental accounting, where loss aversion is the tendency of individuals to be more sensitive to losses than gains and mental accounting is the cognitive activity that individuals perform to evaluate alternatives and take decisions (*20*). In the literature, MLA refers typically to the way individuals evaluate a sequence of long-term risky investments that can also be evaluated in the short-term (*20*, *24*): myopic individuals evaluate the investments independently and reject them if each risky investment is separately unattractive, while non-myopic individuals evaluate the sequence in its entirety and reject the investments only if the aggregated net return is unattractive (*24*). Accordingly, MLA implies that individuals reach different decisions according to the problem framing. Lessening MLA requires limiting evaluation frequency (i.e., the time horizon for investment evaluation) and increasing decision flexibility (i.e., the individual has more ability to adjust the decision).

A UG is a sequential bargaining zero-sum game where the proposer and the responder are two players who bargain on sharing a sum of money: the proposer decides how the money is shared between the two players, and the responder decides to accept or reject the proposed shares (*21*). Accepting implies that each player earns the agreed share, while rejecting entails no earnings for both players. The classical game theory prediction for the bargaining equilibrium solution is that the responder accepts any positive share, regardless of its amount, since this positive share is better than the zero earning associated to the rejection (ceteris paribus), while the proposer expects the responder to act as a rational utility maximizer by offering the smallest positive share. The actual observation of empirical evidence suggests that the amounts proposed and rejected are affected by additional factors such as emotions, feeling of fairness, sense of punishment, sense of reciprocity and, to a lesser extent, demographic and cultural variables (e.g., *25*, *26*).

Consider an individual facing the decision between a first option having cost c at time t and a second option having cost $(c - g)$ at time $(t + \Delta t)$, and hence having a potential gain g from the second option. The gain is potential because the individual is the proposer in a UG where the other player (the responder) earns the cost paid: the individual proposes a value g for choosing the second option, and the responder decides whether to accept or reject the proposal. From the proposer perspective, the acceptance implies a cost $(c - g)$ and hence a gain g, while the rejection entails no gain and a default saving s. From the responder perspective, the acceptance implies lower revenue by the amount g with respect to the rejection. Given the UG, the individual faces two decisions: (i) whether to present the proposal to the responder; (ii) if presenting the proposal, which amount g to propose. Thus, the individual perceives two contrasting motivations towards proposing on the one hand a higher amount, as a higher proposal implies a higher expected gain, and on the other hand a lower amount, as a higher proposal entails also a lower acceptance probability θ of the responder. Moreover, in the case the responder accepts and the individual postpones the decision by Δt, a probability α exists that an unforeseen event occurs at an extra cost e equal to $(g + s)$ for the individual.

Accordingly, there are four possible outcomes from the decision of the individual to present the proposal, the decision of the individual about the amount g, the acceptance probability θ of the responder, and the occurrence probability α of an unforeseen event:

- the individual does not present the proposal, and hence experiences cost *c* and default saving *s* at time *t*;
- the individual proposes an amount *g* that is rejected by the responder, and hence experiences cost *c* and default saving *s* at time *t*;
- the individual proposes an amount *g* that is accepted by the responder and no unforeseen occurs, and hence experiences cost ($c - g$) and extra saving *g* at time ($t + \Delta t$);
- the individual proposes an amount *g* that is accepted by the responder but an unforeseen event occurs, and hence experiences cost ($c - g + e$) and no saving at time ($t + \Delta t$).

The behavioral framework assumes that the individual maximizes the utility $U(g)$:

$$U(g) = \theta\alpha g + (1-\theta)s - \theta(1-\alpha)(e-g) \tag{1}$$

where the first term represents the utility from the gain *g* given the responder acceptance of the proposal and the non-occurrence of the unforeseen event, the second term represents the utility from the saving given the responder rejection of the proposal, and the third term represents the disutility (hence the negative sign) from the extra cost for the occurrence of the unforeseen event.

The acceptance probability θ of the responder depends on the amount *g* proposed by the individual and it is assumed without loss of generality to have a uniform distribution:

$$\theta = \begin{cases} 0 & \text{for } g \geq c \\ \dfrac{c-g}{c} & \text{for } 0 \leq g < c \end{cases} \tag{2}$$

Intuitively, the probability θ is inversely related to the proposed amount *g* in its being higher for lower values of *g*, it is equal to 0 when the proposed amount *g* is equal or higher than the cost *c*, since the responder will never accept not to earn anything, and it is equal to 1 when the proposed amount *g* is equal to 0, since the responder will always accept to earn the full cost *c*.

Given the expression of the acceptance probability θ, the individual maximizes the utility:

$$\begin{aligned} U(g) &= \frac{c-g}{c}\alpha g + \frac{g}{c}s - \frac{c-g}{c}(1-\alpha)(e-g) \\ &= -\frac{1}{c}g^2 + \left(1 + \frac{s+e(1-\alpha)}{c}\right)g + e(\alpha - 1) \end{aligned} \tag{3}$$

Notably, this expression shows the trade-off for the individual facing the decisions of presenting the proposal and eventually choosing the amount *g*: the incentive for the individual to demand a higher amount *g* in order to maximize the utility is compensated by the higher chance of rejection of the proposed amount.

Consider now that the individual repeats *N* decisions and might exhibit myopic loss averse behavior possibly related to either the evaluation of gains and losses over the *N* decisions or the cautiousness in the bargaining with the responder. Given that the behavioral framework represents utility maximizers under MLA within an ultimatum game, there are four boundary conditions: (i) non-myopic behavior without UG framework; (ii) non-myopic behavior within the

UG framework; (iii) myopic behavior without UG framework; (iv) myopic behavior within the UG framework.

The first boundary condition implies that the individual has a degree of loss aversion λ (*24*) and the responder accepts any proposed amount g ($\theta = 1$). Accordingly, the individual maximizes the utility:

$$U(g) = \alpha g - (1-\alpha)(e-g)\lambda = (\alpha + \lambda - \alpha\lambda)g - (1-\alpha)e\lambda \tag{4}$$

The non-myopic individual maximizes the utility by proposing always the maximum possible g equal to c, and is indifferent for g equal to $(1 - \alpha)e\lambda / (\alpha + \lambda - \alpha\lambda)$.

The second boundary condition differentiates from the first only in generalizing the expression of the probability θ, thus the individual maximizes the utility:

$$\begin{aligned} U(g) &= \frac{c-g}{c}\alpha g + \frac{g}{c}s - \frac{c-g}{c}(1-\alpha)(e-g)\lambda \\ &= \frac{(\alpha\lambda - \alpha - \lambda)}{c}g^2 + \left(\alpha + \lambda - \alpha\lambda + \frac{s + e\lambda(1-\alpha)}{c}\right)g + e\lambda(\alpha - 1) \end{aligned} \tag{5}$$

Notably, the utility formulation implies that the higher is the degree of loss aversion λ, the lower is the expected maximized value of the utility function, ceteris paribus, since the loss aversion affects only the disutility from the occurrence of the unforeseen event.

The third boundary condition entails that the individual has a myopic behavior and the responder accepts any proposed amount g ($\theta = 1$). Considering each occurrence v of the unplanned event over the N decisions, the individual maximizes the utility:

$$U(g) = \sum_{v=0}^{N} [a^{N-v}(1-\alpha)^v((N-v)g - v(e-g))]\beta \tag{6}$$

where the parameter β corresponds to the degree of loss aversion λ if $(N - v)g - v(e - g) < 0$, and 1 otherwise.

The fourth boundary condition corresponds to the most generic expression where not only the individual has a myopic behavior, but he also participates to the UG, thus maximizing the utility:

$$U(g) = \sum_{v=0}^{N} [a^{N-v}(1-\alpha)^v\left(\frac{c-g}{c}\right)((N-v)g - v(e-g))]\beta + \frac{Ngs}{c} \tag{7}$$

Last, the behavioral framework differentiates between proposer-controlled and responder-controlled environments. In the former environment, the individual has full information and control over the two options, and the probabilities θ and α represent respectively the aforementioned acceptance probability of the responder and the occurrence probability of the unforeseen event. Accordingly, it is possible to interpret the behavior of the individual as risk averse, neutral or prone. In the latter environment, the individual is aware of the first option, but the responder controls the second option in terms of time Δt and cost $(c - g)$. Accordingly, it is possible to interpret the behavior of the individual as ambiguity averse, neutral, or prone, as the probability θ represent the value of letting the control to the responder rather than selecting the only known option.

EMPIRICAL ANALYSIS

The experimental analysis focused on testing the proposed behavioral framework in the context of EV charging decisions. Specifically, the underlying hypothesis was that EV-owners are not purely utility maximizers, but they are utility maximizers under MLA within a UG framework: the EV-owner is the proposer who faces N decisions about postponing the charging from the peak hour t to the off-peak hour $(t + \Delta t)$ and proposing a discount g on the charging cost c to the responder; the electricity supplier is the responder with probability θ of accepting the discount g; an unplanned trip occurring before the completion of the postponed charging is the unforeseen event with probability α of occurring and extra cost e for a taxi.

Experimental design

The experiment was conducted with the Z-tree program (*27*) at the Centre for Experimental Economics (CEE) of the University of Copenhagen among a sample of 147 individuals recruited within the CEE registered panel. In terms of socio-demographics, 42.2% of the participants were women, the average age was 26.7 years, and the average monthly income was 1430 USD. In terms of education, 25.9% of the participants had a Bachelor degree and 66.7% had a Master degree. In terms of employment, 21.1% of the participants were unemployed, 38.1% were students, 29.9% were students with also an employment, and 10.9% were employees. The participants had previously participated in 2.8 experiments on average.

An SP experiment was designed to investigate utility maximization under MLA within a UG framework. Since SP experiments are susceptible of incentive compatibility bias associated to respondents not bearing the consequences of their choices, and since associating hypothetical decisions with actual transactions is known to mitigate this bias (*28*), the experiment involved actual monetary gains for the participants according to their decisions. Participants earned tokens during the experiment and converted them to cash after its conclusion. They were informed that the compensation would vary between 10 USD, representing a show up fee, and 87 USD, representing the total possible earnings from optimal choices. Participants actually earned between 17 and 51 USD for an average earning of 28 USD in an average duration of 50 min, above the hourly wage for a student job varying between 20 and 24 USD.

Participants were instructed to assume to be EV-owners with home EV charging availability and battery charging time equal to 2 hours. Socio-demographic information was collected, but they were given the same income (110 tokens per day) and mobility pattern in order to avoid biases deriving from heterogeneity in value-of-time and travel activity during peak and off-peak hours. Participants were informed that the car battery empties every day at 6pm when they return home from their mandatory and non-mandatory daily activities, and requires charging before the next mandatory trip the following day at 9am.

Participants faced the decision about whether to pay the amount c for EV charging at time t (6pm) or requesting a discount g to the supplier for postponing the charging by Δt, given that the electricity price depends on the charging hour. Participants entered a UG that was set up by allowing for the probability θ that the supplier accepts the discount g for postponing the EV charging to off-peak hours and hence reducing the grid load, and setting the acceptance or rejection of the amount g and time Δt by the supplier to be compared against randomly drawn threshold values. Participants were informed that, in the case that the supplier agrees with postponing the EV charging, there is a probability α that an unplanned trip will occur before the charging is completed and hence they will have to pay an extra cost e for a taxi ride. The participants were also informed about general conditions: the supplier does not influence the occurrence probability α of the unplanned trip; charging days are independent and hence both probabilities θ and α do not depend from previous decisions of the same participant as well as decisions of other participants; daily earnings are independent and hence outcomes are unaffected by the ones of the same participants in previous days as well as the ones of other participants; decisions are taken individually with participants unaware of the decisions of their peers.

Each participant took part in one of six treatment conditions resulting from the combinations of three decisions and two contract durations (24-25 participants per condition). The assignment to the treatments was completely randomized. The three decisions concerned (i) the willingness to postpone the charging time, (ii) the discount asked to the supplier for postponing the charging, and (iii) the willingness to accept supplier-controlled charging. The two contract durations were (i) daily, where the participants performed 24 decisions representing 24 charging days, and (ii) weekly, where the participants performed only 3 decisions over the 24 charging days (i.e., on days 1, 9 and 17) and each decision was valid for the next 8 charging days. The two contract durations were deemed suitable to elicit myopic versus non-myopic behavior because habitually MLA is tested for 1-day versus 3-day rounds (*29*). The information about the outcome and the corresponding daily earnings was different according to the contract: (i) 24 daily rounds were sent to participants in the daily contracts; (ii) both 3 weekly and 24 daily rounds were sent to participants in the weekly contract. Before starting the experiment, participants answered four control questions to make sure that the level of understanding of the experiment was uniform, and clarifications were given to the small minority not answering correctly to these questions.

Experiment 1: Willingness to postpone the charging time

Procedure

Participants were requested to choose between charging upon arrival home at the peak hour t (6pm) or postponing the charging to off-peak hour ($t + \Delta t$). Charging at peak hour t costs c equal to 100 tokens (default saving s equal to 10 tokens), but it is risk-free because the supplier always accepts its maximum revenue and there is no possibility of unplanned trip. Postponing the charging to off-peak hour ($t + \Delta t$) costs ($c - g$) where the discount g is always 25 tokens regardless of the time Δt, and it is risky because the supplier may reject the proposal since the discount is available only in certain hours randomly selected by the supplier from a uniform distribution. A random number was drawn to simulate the acceptance or rejection by the supplier: if rejected, the participant was required to pay full price c and recharge at 6pm; if accepted, the occurrence probability α of an unplanned trip existed. The probability depends on the charging hour, with the occurrence risk increasing linearly by 2% every 15 minutes. Participants were fully informed about the occurrence probability α of an unplanned trip prior to making the decision and about the taxi fee being e equal to 35 tokens (i.e., the discount g plus the saving s). A random number, independent from the previous one, was drawn to simulate the occurrence or not of the unplanned trip.

In this first experiment, the longer the participants postponed the charging hour, the more likely they were going to obtain the discount g in the negotiation with the supplier, but also the more likely they were going to need a taxi because of the higher occurrence probability of an unplanned trip. This experiment was administered to two groups with daily and weekly contract conditions. Notably, in time-based decisions where respondents are asked to choose between a smaller immediate reward (i.e., the saving *s* of 10 tokens for immediate charging) or a larger delayed reward (i.e., the saving ($g + s$) of 35 tokens for postponed charging), a temporal discounting bias may lead to choosing the immediate reward (*30*). With the aim of lessening this bias and avoid temporal discounting, all the participants received their cash payments only at the end of the experiment.

Results

Table 1 presents the results of the experiment for the two contract conditions. Overall, results illustrate willingness to postpone the EV charging in order to obtain the proposed discount of 25% while risking losses because of a possible unplanned trip before the charging was completed. Peak hour charging, corresponding to a sure saving of 10 tokens and zero probability of an unplanned trip, was chosen only in 63 days (5.7% of the charging days).

TABLE 1 Willingness to Postpone the EV Charging Time

	Average charging hour including the risk-free option (average acceptable risk of an unplanned trip)			Share of days with the risk-free option of charging at 6pm for a fee of 100 tokens		Money earned	
Round	Daily contract	Weekly Contract	Mann-Whitney test	Daily contract	Weekly Contract	Daily contract	Weekly Contract
1	22:12 (37.8%)	22.07 (33.8%)	Z=0.596	18.2%	8.3%	14.0	18.0
1-8	11:42 (46.2%)	22:07 (33.8%)	Z=6.452***	5.1%	8.3%	13.0	14.5
9-16	11:56 (47.5%)	23:10 (41.4%)	Z=2.382**	1.7%	8.3%	13.0	14.0
17-24	11:54 (47.2%)	23:32 (44.3%)	Z=0.456	1.7%	8.3%	11.7	11.7
all	11:50 (47.0%)	22:56 (40.0%)	Z=5.670***	3.0%	8.3%	12.5	13.3

Note: *significant at the 0.10 significance level, **significant at the 0.05 significance level, ***significant at the 0.01 significance level.

In this first experiment, the supplier's acceptance rate depends on the EV-owner's risk level. Utility maximization disregarding myopia and the "cautious player" property would lead to postponing the charging to 10.30pm, corresponding to a 27.8% risk of an unplanned trip and a 27.8% supplier's acceptance probability. Compared with utility maximization, the participants reflect a "cautious player" behavior, namely risk aversion to the possibility that the supplier might reject the proposal, which turns in risk proneness to the unplanned trip. Participants tried to be eligible for discount by postponing EV charging to a later hour while assuming higher risk of an unplanned trip. Compared to participants in weekly contracts, the participants in daily contracts showed myopia in taking higher risk aversion towards supplier rejection by both postponing more trips to off-peak hours and selecting later hours for EV charging. The total average gain of the daily contract is 305.20 tokens, versus 323.27 tokens for the weekly contract and 323.33 tokens for the optimal utility maximizer. These results suggest that participants in weekly contracts approximate utility maximization, while myopic participants in daily contracts have sub-optimal behavior from their perspective, although favorable outcomes from the grid load perspective.

Experiment 2: Acceptable discount for postponing the charging time

Procedure

Participants were requested to select the amount g for postponing the EV charging from the peak hour t (6pm) to the off-peak hour ($t + \Delta t$). As in the first experiment, charging at peak hour t costs c equal to 100 tokens and it is risk-free because the supplier always accepts its maximum revenue and there is no possibility of unplanned trip. In this second experiment, the off-peak hour ($t + \Delta t$) is always 11pm and the discount g is variable, hence the cost ($c - g$) depends on the decision of the participant.

Off-peak charging bears two risks. The first risk is the rejection by the supplier who sets a random maximum value in order for the participant to be eligible for a discount. A random number was drawn to simulate whether the proposed g was lower or equal to the supplier's threshold and hence the discount was accepted by the supplier, with saving ($g + s$) for the participant from the postponed charging. If the discount was rejected, the participant was required to pay full price c and recharge at 6pm. The second risk is the occurrence of an unplanned trip before the EV charging is completed that participants were informed to have probability α equal to 66.67% and cost e equal to 35 tokens. Notably, the occurrence probability α does not depend on the supplier, the proposed discount g, or the decisions of the other participants. A random draw, independent from the previous one, was drawn to simulate the occurrence or not of the unplanned trip. This experiment was administered to two groups with daily and weekly contract conditions.

Results

Table 2 presents the results of the experiment for the two contract conditions. Overall, results show willingness to postpone the EV charging to 11pm in exchange for a monetary gain while risking losses because of a 66.67% probability of occurrence of an unplanned trip before the EV was recharged. Peak hour charging was chosen only in 145 days (11.0% of the total charging days), although guaranteeing a saving s of 10 tokens and no risk of unplanned trip. The share of risk-free choices is higher in this second experiment than in the first. Also, although in the first experiment participants were willing to postpone the charging to 12am in the daily contract and to 11pm in the weekly contract for a discount equal to 25% of the charging fee, in this second experiment participants demanded a greater discount for their willingness to postpone the charging to 11pm. Given the random assignment of participants to the treatments and the same income and activity pattern, there is no reason for a systematic difference in the participants, and hence these findings suggest that either the participants assigned value to the perceived behavioral control over their choices or they were affected significantly by the probability of the unplanned trip. Given that participants agreed to supplier-controlled charging in the third experiment, the second reason seems more likely, also because in the first one the average risk of unplanned trip was assumed to be less than 50%, while the average risk was 66.67% in the second one. Aversion to high risk of unplanned trip might have led not only to a higher share of risk-free choices, but also a higher amount g for postponing to the same or earlier charging than in the first experiment, thus suggesting the importance of EV availability for mobility needs.

Compared to participants in weekly contracts, participants in daily contracts reflect a “cautious player” behavior in choosing the risk-free option in a higher share of days and being risk averse to the possibility that the supplier might reject their proposal. Namely, participants tried to be eligible for discount by requesting lower amounts for postponing their charging while assuming a 66.67% risk of an unplanned trip. The total average gain of the daily contract is 264.50 tokens, compared to 304.50 tokens for the weekly contract and 425.50 tokens for the optimal utility maximizer, suggesting a much larger extent of the myopia leading to sub-optimal behavior from the EV-owner perspective and cost minimization benefit from the supplier perspective.

TABLE 2 Acceptable Discount for Postponing the Charging Time to 11pm

	Average discount requested in tokens (including the risk-free option)			Share of days with the risk-free option of charging at 6pm for a fee of 100 tokens		Money earned	
Round	Daily contract	Weekly Contract	Mann-Whitney test	Daily contract	Weekly Contract	Daily contract	Weekly Contract
1	38.0	33.8	Z = 0.367	11.1%	17.9%	13.0	14.3
1-8	36.6	38.5	Z = -0.130	9.3%	17.9%	10.2	12.2
9-16	34.6	39.7	Z = -2.139**	17.6%	0.0%	10.7	13.2
17-24	34.7	41.0	Z = -2.640***	18.1%	3.6%	12.2	13.9
all	35.3	39.7	Z = -2.788***	15.0%	7.1%	11.1	13.1

Note:*significant at the 0.10 significance level, **significant at the 0.05 significance level, ***significant at the 0.01 significance level

Experiment 3: Acceptable discount for supplier-controlled charging

Procedure

Participants were requested to choose the amount g upon agreeing to supplier-controlled charging in which the supplier decides the optimal charging hour with the aim of optimizing the grid load. Participants could also opt for EV charging at peak hour t at the full cost c equal to 100 tokens and hence do not experience any risk. Participants were informed that the supplier could charge their vehicle at 6pm, 11pm, or 3am, and could decide to let the supplier decide, thus reflecting their inconvenience due to the lack of behavioral control and the ambiguity associated with the supplier-controlled charging.

The second option of agreeing to supplier-controlled charging bears two risks. The first risk is that the supplier rejects the proposal because the amount g is deemed unprofitable. The participants were informed that the supplier sets a random maximum value to be eligible for discount, and a random number draw simulated whether the proposed discount g is lower or equal to the supplier’s threshold. If it is lower or equal, then the discount is granted and the daily earnings are $(g + s)$, otherwise the participants need to charge at 6pm at full price c. The second risk is that, when the supplier charges the EV at 11pm or 3am, there is an occurrence probability α of an unplanned trip before completion of the charging. This probability α did not depend on the supplier, the proposed discount g, or the decisions of other participants, but depended on the charging hour (the later is the charging hour, the higher is α). A random draw, independent from the previous one, simulated the occurrence or not of the unplanned trip that implied a taxi fee e equal to (g + s) to annul every earning for the day. This experiment was administered to two groups with daily and weekly contract conditions.

Results

Table 3 presents the results of the third experiment for the two contract conditions. Results illustrate the willingness to concede control to the supplier over the scheduling of EV charging in exchange for a monetary amount g and hence to agree not to know about the charging hour and the probability of an unplanned trip. Peak hour charging was chosen only in 60 days (5.4% of the total charging days) regardless of the sure saving s of 10 tokens and the risk-free conditions. Practically, the participants were willing to wave their perceived behavioral control and deal with an ambiguous and ill-defined EV charging environment where the supplier has complete control. Interestingly, the share of risk-free charging days was similar to the first experiment and lower than the second one, reflecting the possibility that the participants hypothesized the risk of an unplanned trip being lower than 50%.

Compared with the participants in weekly contracts, participants in daily contracts reflected higher "ambiguity aversion" in that they had a higher share of risk-free days and demanded higher amounts g for willing to accept an ambiguous supplier-controlled charging environment. The "ambiguity aversion" in this third experiment is a more dominant behavioral rule over the "cautious player" behavior observed in the previous two experiments. Also, the weekly contract produces a favorable outcome in terms of costs assumed by the supplier.

TABLE 3 Acceptable Discount for Supplier-Controlled Charging

	Average discount requested in tokens			Share of days with the risk-free option of charging at 6pm for a fee of 100 tokens		Money earned in tokens per round	
Round	Daily contract	Weekly Contract	Mann-Whitney test	Daily contract	Weekly Contract	Daily contract	Weekly Contract
1	32.9	32.9	Z = -0.056	10.0%	19.2%	20.5	15.2
1-8	34.4	32.9	Z = 0.267	5.0%	19.2%	16.9	16.0
9-16	38.2	38.0	Z = 0.152	5.6%	0.0%	14.5	17.2
17-24	44.6	39.2	Z = 3.350***	2.0%	0.0%	19.4	15.1
All	39.1	36.7	Z = 2.141**	4.2%	6.4%	16.9	16.1

Note:*significant at the 0.10 significance level, **significant at the 0.05 significance level, ***significant at the 0.01 significance level

CONCLUSIONS

This study proposes a novel behavioral framework representing utility maximization under MLA in the context of a two-player UG and presents an application to represent the charging decisions of EV-owners. The EV-owners' charging choice behavior is explored for three stipulated choices (willingness to postpone their charging to off-peak hours, requested discount fee for off-peak charging, and requested discount fee for accepting supplier-controlled charging) and two contract conditions (daily and weekly) by means of an SP experimental analysis.

A word of caution is warranted for result interpretation and policy implementation. Firstly, this study was conducted in laboratory conditions and although it controlled for incentive compatibility and temporal discounting biases, the conditions do not reflect the actual electricity costs and mobility needs. Secondly, this study assumes a stylized experimental design with population homogeneity in terms of value of time, mobility needs, battery charging preferences, car availability and size. Thirdly, this study was conducted with participants without prior experience as EV-owners or users, while a recent study shows that EV user experience results in attitudinal change in SP choice experiments (*31*). Last, the decisions in the experiment were taken individually and the participants were unaware of the decisions of their peers, while in reality word-of-mouth is a powerful market force. Therefore, the results should be viewed as an indicative or diagnostic tool rather than a statistical analysis of the prevalence of the identified themes across the population of potential EV-owners and cannot be readily extended for the purpose of demand analysis.

Bearing these limitations in mind, this study provides valuable insights for decision-makers and planners in the transportation and energy fields and these insights may be integrated into agent-based and optimization models relying on behavioral rules regarding EV-owners' charging behavior.

Firstly, the empirical results show high willingness of EV-owners to postpone charging hour from peak to off-peak hours as well as to concede control of the charging environment to the supplier. This finding indicates consumer openness towards centralized smart-grid strategies that can optimize the load on the electricity grid from a system optimum perspective. A discount of 25% on the full charging fee is deemed highly attractive for postponing the charging hour to off-peak period (between 11pm and 12am) while assuming between 40% and 47% of a risk of an unplanned trip with a cost of 35% of the charging fee. The requested discount for a supplier-controlled environment in which the charging hour and the risk of an unplanned trip are unknown to the EV-owner varies between 35% and 40%, which indicates the value of inconvenience due to ambiguity.

Secondly, the empirical results confirm the proposed behavioral model indicating that EV-owners take their decisions about EV charging hours according to utility maximization under MLA in the context of a UG. This behavior translates into risk aversion because of the MLA and the "cautious player" property, as well as the "ambiguity aversion" in the case of ill-defined supplier-controlled charging environment. This behavioral model could be considered to substitute the unrealistic and yet constantly used utility maximization in future agent-based and optimization models aiming at providing the system optimum electricity load.

Last, the type of contract conditions and hence the frequency of charging decisions (daily versus weekly) is related to utility maximization under MLA in the context of a two-player UG and can be used to either encourage consumer's utility maximization or supplier's cost minimization. Participants in the weekly contracts approximate utility maximization (especially in the decision to postpone or not the charging), while the myopia of the participants in the daily contracts leads to sub-optimal behavior from the EV-owner perspective but also to favorable outcomes in terms of grid load from the electricity supplier perspective. Compared to participants in weekly contracts, participants in daily contracts were willing to postpone their charging to a later off-peak hour and requested lower compensation for postponing their charging hour, but in contrast they showed higher ambiguity aversion and requested higher compensation for supplier-controlled charging.

ACKNOWLEDGMENTS

The authors gratefully acknowledge that the study forms part of the project “Consumer acceptance of intelligent charging” funded by the ForskEL program of the Danish Ministry for Climate and Energy.

REFERENCES

1. Dagsvik, J.K., T. Wennemo, D.G. Wetterwald, and R. Aaberge. Potential demand for alternative fuel vehicles. *Transportation Research Part B: Methodological*, Vol. 36, 2002, pp. 361-384.
2. Brady, J., O’Mahony, M. Travel to work in Dublin: The potential impacts of electric vehicles on climate change and urban air quality. *Transportation Research Part D: Transport and Environment*, Vol. 16, 2011, pp. 188-193.
3. Mendes Lopes, M., F. Moura, and L.M. Martinez. Rule-based approach for determining the plausible universe of electric vehicle buyers in the Lisbon Metropolitan Area. *Transportation Research Part A: Policy and Practice,* Vol. 59, 2014, pp. 22-36.
4. Lebeau, K. J. van Mierlo, P. Lebeau, O. Mairesse, and C. Macharis. The market potential for plug-in hybrid and battery electric vehicles in Flanders: A choice-based conjoint analysis. *Transportation Research Part D: Transport and Environment*, Vol. 17, 2012, pp. 592-597.
5. Mabit, S.L., and M. Fosgerau. Demand for alternative-fuel vehicles when registration taxes are high. *Transportation Research Part D: Transport and Environment*, Vol. 16, 2011, pp. 225-231.
6. Shafiei, E., H. Thorkelsson, E.I. Ásgeirsson, B. Davidsdottir, R. Raberto, and H. Stefansson. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. *Technological Forecasting & Social Change*, Vol. 79, 2012, pp. 1638-1653.
7. Traut, E.J., T.W.C. Cherng, C. Hendrickson, and J.J. Michalek. US residential charging potential for electric vehicles. *Transportation Research Part D: Transport and Environment*, Vol. 25, 2013, pp. 139-145.
8. Amoroso, F.A., and G. Cappuccino. Advantages of efficiency-aware smart charging strategies for PEVs. *Energy Conversion and Management*, Vol. 54, 2012, pp. 1-6.
9. Axsen, J., and K.S. Kurani. Anticipating plug-in hybrid vehicle energy impacts in California: constructing EV-owner-informed recharge profiles. *Transportation Research Part D: Transport and Environment*, Vol. 15, 2010, pp. 212-219.
10. Finn, P., C. Fitzpatrick, and D. Connolly. Demand side management of electric car charging: Benefits for consumer and grid. *Energy*, Vol. 42, 2012, pp. 358-363.
11. Kiviluoma, J., and P. Meibom. Methodology for modelling plug-in electric vehicles in the power system and cost estimates for a system with either smart or dumb electric vehicles. *Energy*, Vol. 36, 2011, pp. 1758-1767.
12. Lyon, T.P., M. Michelin, A. Jongejan, and T. Leahy. Is ‘‘smart charging’’policy for electric vehicles worth while? *Energy Policy*, Vol. 41, 2012, pp. 259-268.

13. Pelzer, D., D. Ciechanowicz, H. Aydt, and A. Knoll. price-responsive dispatching strategy for Vehicle-to-Grid: An economic evaluation applied to the case of Singapore. *Journal of Power Sources*, Vol. 256, 2014, pp. 345-353.

14. Dallinger, D., and M. Wietschel. Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles. *Renewable and Sustainable Energy Reviews*, Vol. 16, 2012, pp. 3370-3382.

15. Waraich, R.A., M.D. Galus, C. Dobler, M. Balmer, G. Andersson, and K.W. Axhausen. Plug-in hybrid electric vehicles and smart grids: Investigations based on a micro-simulation. *Transportation Research Part C: Emerging Technologies*, Vol. 28, 2013, pp. 74-86.

16. Di Giorgio, A, Liberati F., Canale, S. Electric vehicles charging control in a smart grid: A model predictive control approach. *Control Engineering Practice*, Vol. 22, 2014, pp. 147-162.

17. Iversen, E.B., J.M. Morales, and H. Madsen. Optimal charging of an electric vehicle using a Markov decision process. *Applied Energy*, Vol. 123, 2014, pp. 1-12.

18. Franke, T., and J.F. Krems. Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 21, 2013, pp. 75-89.

19. Caperello, N., K.S. Kurani, and J. TyreeHageman. Do you mind if I plug-in my car? How etiquette shapes PEV drivers' vehicle charging behavior. *Transportation Research Part A: Policy and Practice*, Vol. 54, 2013, pp. 155-163.

20. Benartzi, S., and R.H. Thaler. Myopic Loss Aversion and the equity premium puzzle. *The Quarterly Journal of Economics*, Vol. 110, 1995, pp. 73-92.

21. Kagel, J.H., C. Kim, and D. Moser. Fairness in ultimatum games with asymmetric information and asymmetric payoffs. *Games and Economic Behavior*, Vol. 13, 1996, pp. 100-110.

22. Driesen, B., A. Perea, and H. Peters. On loss aversion in bimatrix games. *Theory and Decision*, Vol. 68, 2010, pp. 367-391.

23. Rajagopal,P., and J.Y. Rha. The mental accounting of time. *Journal of Economic Psychology*, Vol. 30, 2009, pp. 772-781.

24. Thaler, R.H., A. Tversky, D. Kahneman, and A. Schwartz. The effect of myopia and loss aversion on risk taking: An experimental test. *The Quarterly Journal of Economics*, Vol. 112, 1997, pp. 647-661.

25. Camerer, C., and R.H. Thaler. (1995). Anomalies: Ultimatums, dictators and manners. *Journal of Economic Perspectives*, Vol. 9, 1995, pp. 209-219.

26. Van't Wout, M., R.S. Kahn, A.G. Sanfey, and A. Aleman. Affective state and decision-making in the ultimatum game. *Experimental Brain Research*, Vol. 169, 2006, pp. 564-568.

27. Fischbacher, U. z-tree: Zurich toolbox for ready-made economic experiments. *Experi- mental Economics*, Vol. 10, 2007, pp. 171-178.

28. Wang, T., R. Venkatesh, and R. Chatterjee. Reservation price as a range: an incentive compatible measurement approach. *Journal of Marketing Research*, Vol. 44, 2007, pp. 200-213.

29. Hardin, A.M., and C.A. Looney. Myopic loss aversion: Demystifying the key factors in influencing decision problem framing. *Organizational Behavior and Human Decision Processes*, Vol. 117, 2012, pp. 311-331.

30. Read, D. Intertemporal choice. In: (eds. Koehler, D.J., and N. Harvey), *Blackwell Handbook of Judgment and Decision Making*, Blackwell Publishing, Malden, MA, 2004.

31. Jensen, A.F., E. Cherchi, and S.L. Mabit. On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment*, Vol. 25, 2013, pp. 24-32.